Cross-modality Face Recognition via Heterogeneous Joint Bayesian

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***Abstract*— In many face recognition applications, the modalities of face images between the gallery and probe sets are different, which is known as heterogeneous face recognition. How to reduce the feature gap between images from different modalities is a critical issue to develop highly accurate face recognition algorithm. Recently, Joint Bayesian (JB) has demonstrated superior performance on general face recognition compared to traditional discriminant analysis methods like subspace learning. However, the original JB treats the two input samples equally and does not take into account the modality difference between them and may be sub-optimal to address the heterogeneous face recognition problem. In this work, we extend the original JB by modeling the gallery and probe images using two different Gaussian distributions to propose a Heterogeneous Joint Bayesian (HJB) formulation for cross-modality face recognition. The proposed HJB explicitly models the modality difference of image pairs and therefore is able to better discriminate the same/different face pairs accurately. Extensive experiments conducted in the case of VIS-NIR and ID photo vs. spot face recognition problems show the superiority of HJB over previous methods.**

***Index Terms*—Cross Modality, Heterogeneous Face Recognition, Joint Bayesian.**

I. Introduction

Heterogeneous face recognition is a common issue in many face recognition applications, where the gallery and the probe face images come from different modalities. For example, in the application of access control, the gallery is usually controlled visible (VIS) photo, while the probe sometimes prefers to be near-infrared (NIR) image which is robust to illumination variations [1]. This is a cross-modality face recognition problem between VIS and NIR face images. In the remote face verification, which is increased in recent years, the gallery is usually the ID photo captured in the constrained condition, while the probe is the face image captured by cellphone or webcam in a more arbitrary environment, which contains more variations of lighting, pose, expression, accessory *etc*.

Up to now, many approaches have been proposed to address the heterogeneous face recognition problem. One category is to extract modality-invariant features to reduce the feature gap between different modalities so that the face images from different modalities can be well matched. Liao *et al.* [2] uses DoG to obtain the normalized appearances from different modalities, and uses MB-LBP to extract discriminative features. Zhang *et al.* [3] proposes a face descriptor based on coupled information-theoretic encoding to capture the local face structure of photo and sketch face images. Liu *et al.* [4] derives light source invariant features to extract invariant parts between the different modalities. Lei *et al.* [5] extends the discriminative local features in a coupled way to reduce the difference between features of heterogeneous face images.

Another sort of methods focus on coupled metric or classifier learning. Lin *et al.* [6] proposes to learn two transforms simultaneously and transform the inputs from different modalities to a common features space. LSR-LDA [7] copes with the irregular distribution of heterogeneous face data to improve the conventional LDA. Lei *et al.* [8], [9] propose to learn two coupled projections to map the face images from different modalities to a common subspace in which good discrimination can be gained. Klare *et al.* [10], [11] try to learn multiple projections for forensic sketch-photo matching. MCA [12] uses a learned generative model to infer the mutual components of different modalities.

Besides, researchers also propose to deal with heterogeneous face recognition in an analysis-by-synthesis way. Face Analogy [13] performs heterogeneous face matching by transforming face images from one modality to another. Xu *et al.* [14] proposes to reconstruct face image from each other modality by using a learnt ℓ-0 minimization based dictionary. Other methods [15], [16] apply the depth information and LBP to accomplish the recognition task.

In recent years, deep learning methods have achieved great success in many computer vision tasks including face recognition. Certain deep convolutional neural network (CNN) models have been successively applied for general face recognition, such as DeepID2 [17], VGG Face [18] *etc.* There are also some pioneering works to address cross-modality face recognition by using deep learning methods. Yi *et al.* [19] uses the Gabor feature and RBM to learn shared representation in order to reduce the heterogeneity in the encoder layer. Ensemble ELM [20] and MTC-ELM [21] employ the extreme learning machine for the feature learning of cross-modality face images. TRIVET [22] pretrains a deep CNN on a large dataset of general human face, and finetunes it on the heterogenous face dataset.

Recently, the Joint Bayesian (JB) [23] method is proposed to model the intra and inter face pairs effectively for general face recognition. As a metric learning method, the JB method achieves superior accuracies of recognition with both the traditional features [23] and the deep learning features [17]. However, the JB method does not take into account the heterogeneity in cross-modality face recognition. Inspired by the effectiveness of the JB method, we extend it to the range

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This work was supported by the National Key Research and Development Plan (Grant No.2016YFC0801002), the Chinese National Natural Science Foundation Projects #61473291, #61572501, #61502491, #61572536, and AuthenMetric R&D Funds.

of heterogeneous face recognition.

To this end, in this paper, we reformulate the JB method in an asymmetric form, namely Heterogeneous Join Bayesian (HJB), in which the heterogeneity is taken into account for learning a more effective metric across different modalities. The HJB considers the two inputs as the samplings from two different Gaussian distributions, and optimize the asymmetric metric with respect to the log likelihood ratio across modalities. In this way, HJB surpasses the baseline JB, and achieves the state-of-the-art performance for the heterogeneous face recognition. Extensive experiments on NIR-VIS and ID photo vs. spot faces validate the superiority of HJB[1].

The remainder of this paper is organized as follows. In Section II, we revisit the ordinary JB method. In Section III, we introduce the novel formulation of HJB and its solution using the expectation maximization (EM) method. In Section IV, we conduct the comparison of HJB with previous methods on several benchmarks of NIR vs. VIS and ID vs. spot face recognition. We conclude the paper in Section V.

II. Revisit of Joint Bayesian

Let x be the representation of human face image. x is supposed to be comprised by two independent random variables μ and ϵ, *i.e.* $x = \mu + \epsilon$. The variable μ and ϵ represents the identity and the intra-class variations (*e.g.* pose, expression, illumination *etc.*). As described in the previous works [24], [25], μ and ϵ can be regarded as two independent zero-mean Gaussian variables, *i.e.* $\mu \sim \mathcal{N}(0, S_\mu)$ and $\epsilon \sim \mathcal{N}(0, S_\epsilon)$. As the sum of μ and ϵ, x follows the Gaussian distribution $\mathcal{N}(0, S_\mu + S_\epsilon)$ as well. Consider two inputs x_1 and x_2, their joint distribution is also gaussian. Denote H_I the hypothesis the two inputs belong to the same subject, and H_E the hypothesis of different subjects. One can write the covariance matrix of the intra-class joint distribution $P(x_1, x_2|H_I)$ as

$$\Sigma_I = \begin{bmatrix} S_\mu + S_\epsilon & S_\mu \\ S_\mu & S_\mu + S_\epsilon \end{bmatrix}, \tag{1}$$

and the counterpart of the inter-class joint distribution $P(x_1, x_2|H_E)$ as

$$\Sigma_E = \begin{bmatrix} S_\mu + S_\epsilon & 0 \\ 0 & S_\mu + S_\epsilon \end{bmatrix}. \tag{2}$$

The assumption behind this neat formulation is that the identity μ and the intra-class variations ϵ are independent. To measure the similarity between x_1 and x_2, the log likelihood ratio is computed by

$$r(x_1, x_2) = log\frac{P(x_1, x_2|H_I)}{P(x_1, x_2|H_E)} = x_1^T A x_1 + x_2^T A x_2 - 2x_1^T G x_2. \tag{3}$$

One can refer to the original proposal [23] for the calculation details of the matrices A and G.

III. Heterogeneous Joint Bayesian

In this section, we introduce the asymmetric formulation of HJB and the solution via EM algorithm.

[1]The source code of HJB will be released at http://www.cbsr.ia.ac.cn/users/hailinshi/

A. Asymmetric Model

By breaking the x_1-x_2 symmetry in the original JB, we introduce the gallery x and the probe y as two different random variables, and their decompositions as $x = \mu_x + \epsilon_x$ and $y = \mu_y + \epsilon_y$. The variables μ_x, μ_y are the identity variations, ϵ_x, and ϵ_y are the intra-class variations, all of which follow the zero-mean gaussians, *i.e.* $\mu_x \sim \mathcal{N}(0, S_{xx})$, $\mu_y \sim \mathcal{N}(0, S_{yy})$, $\epsilon_y \sim \mathcal{N}(0, T_{xx})$ and $\epsilon_x \sim \mathcal{N}(0, T_{yy})$. Here, S_{xx}, S_{yy}, T_{xx} and T_{yy} are the corresponding covariances respectively. To reveal the connection between the gallery and probe, we introduce the covariance of the cross-modality identity variations between x and y as

$$S_{xy} = cov(\mu_x, \mu_y), \tag{4}$$

$$S_{yx} = cov(\mu_y, \mu_x), \tag{5}$$

which are mutual transposes $S_{xy} = S_{yx}^T$. The $cov(\cdot, \cdot)$ denotes the covariance. Consequently, the covariance matrix of the intra-class joint distribution $P(x, y|H_I)$ is written as

$$\Sigma_I = \begin{bmatrix} S_{xx} + T_{xx} & S_{xy} \\ S_{yx} & S_{yy} + T_{yy} \end{bmatrix}, \tag{6}$$

and the counterpart of the inter-class joint distribution $P(x, y|H_E)$ is written as

$$\Sigma_E = \begin{bmatrix} S_{xx} + T_{xx} & 0 \\ 0 & S_{yy} + T_{yy} \end{bmatrix}. \tag{7}$$

With these covariance matrices, we revise the cross-modality log likelihood ratio of x and y as

$$r(x, y) = log\frac{P(x, y|H_I)}{P(x, y|H_E)} = x^T A x + y^T B y - 2x^T G y, \tag{8}$$

where

$$A = (S_{xx} + T_{xx})^{-1} - E, \tag{9}$$

$$B = (S_{yy} + T_{yy})^{-1} - F, \tag{10}$$

$$\begin{bmatrix} E & G \\ G^T & F \end{bmatrix} = \begin{bmatrix} S_{xx} + T_{xx} & S_{xy} \\ S_{yx} & S_{yy} + T_{yy} \end{bmatrix}^{-1}. \tag{11}$$

B. Solution

Based on the learning process in [23], we develop the EM-fashion algorithm to estimate the covariances S_{xx}, S_{yy}, T_{xx}, T_{yy} and S_{xy} for each modality separately.

1) E-step: We introduce two latent variables $\mathbf{h}_x$ and $\mathbf{h}_y$, composed by $\mathbf{h}_x = \left[\mu_x, \epsilon_{x,1}, \ldots, \epsilon_{x,n_g}\right]^T$ and $\mathbf{h}_y = \left[\mu_y, \epsilon_{y,1}, \ldots, \epsilon_{y,n_p}\right]^T$, corresponding to the galleries $\mathbf{x} = \left[x_1, \ldots, x_{n_g}\right]^T$ and probes $\mathbf{y} = \left[y_1, \ldots, y_{n_p}\right]^T$, respectively, of each subject.

Considering the decomposition of identity variations and intra-class variations, the galleries and the probes can be represented by the latent variables as $\mathbf{x} = \mathbf{P}_x\mathbf{h}_x$ and $\mathbf{y} = \mathbf{P}_y\mathbf{h}_y$, where $\mathbf{P}_x$ and $\mathbf{P}_y$ are the matrices with the form of $\begin{bmatrix} \mathbf{I} & \mathbf{I} & 0 & \ldots & 0 \\ \mathbf{I} & 0 & \mathbf{I} & \ldots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \mathbf{I} & 0 & 0 & \ldots & \mathbf{I} \end{bmatrix}$. $\mathbf{I}$ is identity matrix. Obviously, the latent variables also follow the gaussian distributions. Based on

the algorithm in [23], we compute the expectation of latent variables in each modality by

$$E(\mathbf{h}_x|\mathbf{x}) = \Sigma_{\mathbf{h}_x}\mathbf{P}_x^T\Sigma_x^{-1}\mathbf{x}$$
$$= \begin{bmatrix} S_{xx} & 0 & \dots & 0 \\ 0 & T_{xx} & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & T_{xx} \end{bmatrix} \begin{bmatrix} \mathbf{I} & \mathbf{I} & \dots & \mathbf{I} \\ \mathbf{I} & 0 & \dots & 0 \\ 0 & \mathbf{I} & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \mathbf{I} \end{bmatrix}$$
$$\begin{bmatrix} S_{xx}+T_{xx} & S_{xx} & \dots & S_{xx} \\ S_{xx} & S_{xx}+T_{xx} & \dots & S_{xx} \\ \vdots & \vdots & \ddots & \vdots \\ S_{xx} & S_{xx} & \dots & S_{xx}+T_{xx} \end{bmatrix}^{-1} \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_{n_g} \end{bmatrix}, \tag{12}$$

$$E(\mathbf{h}_y|\mathbf{y}) = \Sigma_{\mathbf{h}_y}\mathbf{P}_y^T\Sigma_y^{-1}\mathbf{y}$$
$$= \begin{bmatrix} S_{yy} & 0 & \dots & 0 \\ 0 & T_{yy} & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & T_{yy} \end{bmatrix} \begin{bmatrix} \mathbf{I} & \mathbf{I} & \dots & \mathbf{I} \\ \mathbf{I} & 0 & \dots & 0 \\ 0 & \mathbf{I} & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \mathbf{I} \end{bmatrix}$$
$$\begin{bmatrix} S_{yy}+T_{yy} & S_{yy} & \dots & S_{yy} \\ S_{yy} & S_{yy}+T_{yy} & \dots & S_{yy} \\ \vdots & \vdots & \ddots & \vdots \\ S_{yy} & S_{yy} & \dots & S_{yy}+T_{yy} \end{bmatrix}^{-1} \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_{n_p} \end{bmatrix}. \tag{13}$$

On the right side of Equation (12) and (13), $\Sigma_{\mathbf{h}_x}$ and $\Sigma_{\mathbf{h}_y}$ are the covariances of the latent variables $\mathbf{h}_x$ and $\mathbf{h}_y$. Σ_x is the covariance matrix of the joint distribution of the intra-class set $\mathbf{x}$. Σ_y is the counterpart for $\mathbf{y}$. To start the E-step, the parameters S_{xx}, S_{yy}, T_{xx} and T_{yy} are initialized by the inter- and intra-class covariances of the training set.

2) M-step: Once the latent variables $\mathbf{h}_x$ and $\mathbf{h}_y$ are estimated in the E-step, we compute the covariances of μ_x, μ_y, ϵ_x, and ϵ_y, and use them to update the parameters, *i.e.* $S_{xx} = cov(\mu_x, \mu_x)$, $S_{yy} = cov(\mu_y, \mu_y)$, $T_{xx} = cov(\epsilon_x, \epsilon_x)$, $T_{yy} = cov(\epsilon_y, \epsilon_y)$ and $S_{xy} = cov(\mu_x, \mu_y)$.

We train the model with the EM algorithm for a few iterations when the algorithm converges (generally in 2 iterations). Then, we use the formulas (9), (10) and (11) to compute the model components A, B and G, and the log likelihood ratio (Equation (8)) for testing.

IV. Experiments

We examine the performance of HJB compared with the previous methods including LCKS-CSR [26], MTC-ELM [21], NIR-VIS Reconstruction + UDP (DLBP) [14] and other state-of-the art methods on three databases, *i.e.*, CASIA-HFB [26], CASIA NIR-VIS 2.0 [27] and a private database consisting of ID photo and spot face images.

A. Experiments on CASIA-HFB

CASIA HFB contains 300 subjects, with around 5 NIR images and 5 VIS images per subject. In this part, we follow the same protocol as in [26]. We use the images from the first 150 persons to form the training set and the left images to form the testing set. All the images are cropped into 32x32 gray images according automatically detected eye locations. Some cropped examples are shown in Fig. 1. The pixel intensity is directly used as input. In testing, the VIS images are used as the gallery set and the NIR ones are used as the probe set.

	Rank-1 Accuracy	VR @FAR=10%	VR @FAR=1%	VR @FAR=0.1%
LDA [24]	72.43%	48.75%	26.55%	14.04%
CDFE [6]	16.10%	40.05%	12.75%	3.41%
LDA + CCA [28]	72.65%	42.90%	25.76%	13.79%
LCSR [8]	81.12%	71.28%	51.07%	33.98%
LCKS-CDA [26]	73.18%	54.11%	31.21%	16.61%
LCKS-CSR [26]	81.43%	75.18%	54.81%	**35.69**%
JB	82.30%	73.75%	50.31%	18.19%
HJB	**85.49**%	**80.82**%	**59.30**%	33.65%

TABLE I: Performance comparison with the previous methods on CASIA-HFB.

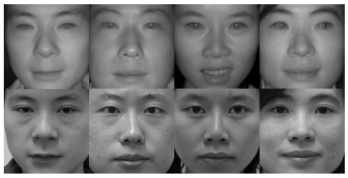


Fig. 1: CASIA-HFB database. Top: NIR images. Bottom: VIS images. Each column belongs to an identity.

We compare HJB method with previous methods including traditional homogenous method like LDA [24] and heterogeneous face recognition methods including LCSR [8], LDA + CCA [28], CDFE [6], LCKS-CDA [26] and LCKS-CSR [26] methods. The face recognition is evaluated in terms of rank-1 accuracy and ROC performance.

Table I shows the rank-1 accuracy and verification rate (VR) at different rate of false accept rate (FAR). From the results, one can see that:

- For the homogeneous face recognition methods, the original JB achieves better performance than LDA, indicating that JB has good ability as a baseline for the heterogeneous face recognition. This leads to the basic motivation that we develop heterogeneous Joint Bayesian to exploit its advantage.
- Comparing HJB with JB, one can see that HJB achieves significantly better performance than JB, especially at the low FAR. HJB enhances JB about 7 to 15 percents in verification rate with different FARs. It validates HJB does improve the heterogeneous face recognition performance by taking into account the modality difference in learning process.
- HJB outperforms previous heterogeneous face recognition methods in most cases. It improves about 4 percents over the previously best method (LCKS-CSR), validating HJB is an effective method to address heterogeneous face recognition problem.

	Rank-1 Accuracy	VR@FAR=0.1%
Cognitec [29]	$58.56 \pm 1.19\%$	N/A
CDFL [30]	$71.5 \pm 1.4\%$	55.1%
DSIFT + LDA [29]	$73.28 \pm 1.10\%$	N/A
Gabor + RBM [19]	$86.16 \pm 0.98\%$	$81.29 \pm 1.82\%$
NIR-VIS Reconstruction + UDP (DLBP) [14]	$78.46 \pm 1.67\%$	85.80%
MTC-ELM [21]	89.1%	N/A
TRIVET [22]	$\mathbf{95.7} \pm 0.5\%$	$\mathbf{91.0} \pm 1.3\%$
Gabor + JB	$89.45 \pm 0.79\%$	$83.28 \pm 1.03\%$
Gabor + HJB	$\mathbf{91.65} \pm 0.89\%$	$\mathbf{89.91} \pm 0.97\%$

TABLE II: Performance comparison with the state of the art on CASIA NIR-VIS 2.0.

B. Experiments on CASIA NIR-VIS 2.0

The CASIA NIR-VIS 2.0 [27] is the largest and most popular database for the NIR-VIS face recognition task. It contains 725 subjects, each of which has 1-22 VIS and 5-50 NIR face images. Under the View2 protocol, the evaluation is performed via the 10-fold process, In each fold, there are 357 subjects for training, and the remaining 358 subjects for test. We compare the proposed HJB with the previous methods which give the state-of-the-art performances on CASIA NIR-VIS 2.0. Considering the good performance in [19], we use the local Gabor features as the inputs of the proposed HJB. We also compare the performance of our HJB with the baselines, *i.e.* the original JB.

Table II shows the performance of different methods on NIR-VIS 2.0 database. The result reveals that:

- The general face recognition method proposed by Cognitec gives poor performances compared with the heterogeneous methods. It is critical to take into account the difference between modalities for heterogeneous face recognition.
- Compared with Gabor + RBM [19], Gabor + HJB gains significantly better performance. It improves the RBM method by about 5 percents in both rank-1 and verification performance, validating the superiority of HJB compared to RBM.
- HJB outperforms the previous state-of-the-art methods except the method TRIVET which trains a deep CNN on a large out-side dataset. Without any help of CNN, our HJB shows its effectiveness for the heterogeneous face recognition.

C. Experiments on ID vs. spot recognition

To further evaluate the HJB, we collect an ID vs. spot face dataset, with 10,000 identities in it. Each identity has an ID photo and a spot photo (Fig. 2). The ID photos and the spot photos are captured under different conditions (*i.e.* the lightening, background, pose *etc.*). This is a very challenging dataset due to the significant difference between the modalities, and the large variations in the spot set.

Because each subject has only one ID photo (gallery) and one spot photo (probe), we are not able to estimate the intra-class covariances ϵ_x and ϵ_y. Instead, we suppose ϵ_x and ϵ_y are not random but determined entities. Therefore, the components

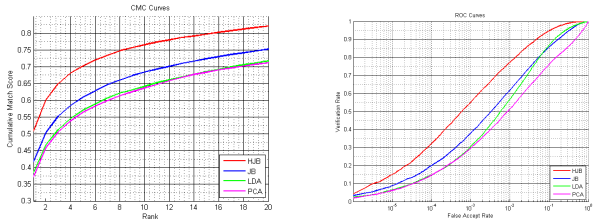
Fig. 2: Top: ID photos. Bottom: Spot photos. Each column belongs to an identity.

	Rank-1 Accuracy	VR @FAR=10%	VR @FAR=1%	VR @FAR=0.1%
Cosine similarity	37.22%	76.07%	51.21%	29.67%
LDA	38.36%	86.65%	56.66%	30.50%
JB	41.64%	85.67%	61.75%	38.13%
HJB	$\mathbf{50.82}\%$	$\mathbf{94.74}\%$	$\mathbf{77.29}\%$	$\mathbf{55.10}\%$

TABLE III: Performances on ID vs. spot.

T_{xx} and T_{yy} vanish in the relevant computation, keeping the rest part unchanged.

To perform the evaluation, we divide the dataset into 10 subsets with non-overlapping, equal number of subjects in each. Then, the 10-fold cross-validation is performed. In each fold, 9 subsets are used for training, and the remaining one is used for test. We apply the features extracted by the model from Yi *et al.* [31] as the input for this experiment.



(a) CMC (b) ROC

Fig. 3: CMC curves and ROC curves on the ID vs. spot recognition task.

Table III lists the performance of different methods whose corresponding CMC and ROC curves are shown in Fig. 3. Four methods, including cosine similarity, LDA, JB and HJB, are compared. As expected, LDA, JB and HJB, which learn discriminative metric, achieve higher face recognition performance than cosine similarity. HJB, which models the modality differences, achieves the best and improves JB by a large margin.

V. Conclusion

In this paper, we develop an asymmetric formulation from Joint Bayesian model for heterogeneous face recognition. The modality difference is involed so the HJB is more adaptive to cross-modality face matching. The metric is learned via optimizing the parameters in each modality separately. We evaluate the HJB on the benchmarks of CASIA-HFB and CASIA NIR-VIS 2.0, and obtain better results than the baseline JB and most other existing methods. The effectiveness of HJB is also validated in the case of ID vs. spot photo recognition.

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